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14. ABSTRACT
The project objectives are to merge population mobility functions with an outbreak detection and characterization capability. The main areas of focus include development of techniques and technology to represent travel modes to and from the study community, and working with local stakeholders to establish the needed information sources within the healthcare, transportation, and hospitality industries. The community survey element of the research includes negotiating access to necessary and minimal datasets and documenting issues and potential impediments that must be addressed to enable such access.
The development and integration of mobility capabilities are fundamental functional requirements for a fully operational biosurveillance system, and by extension, for effective epidemiology in the computer age. This program is progressing in the effort to develop, demonstrate, and validate such functionality.

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1.0 Introduction

The project seeks to identify and evaluate methods for integration of population movement information with detection and characterization functions. Significant efforts include negotiating with local healthcare, transportation and hospitality industry stakeholders to secure the needed information sources, and the development of detection software codes and predictive models. The project has established interface agreements and obtained and integrated data needed for situational awareness from members of the hospitality industry, from transportation industry sources, and from health care providers.

Several hypotheses were investigated as related to the project objectives. The principal hypothesis under test is that situational awareness and response can be improved by the integration of population and population mobility information with health monitoring and tracking functions. Therefore, this research is focused on investigating methods and technologies useful to reduce the impact of pandemic disease or bio-weapon attack though information integration, signal improvement and noise reduction. The study has made progress in developing and validating models and developing and testing algorithms and codes to improve representation of population dynamics in outbreak modeling and surveillance.

2.0 Body

Currently resource constraints, privacy, business competition, and liability issues prevent us from strengthening biosurveillance signals for detection and characterization of outbreaks and attacks. Therefore, much outbreak surveillance research, and existing applications for monitoring and reporting are focused on the sparse data problem, the related signal-to-noise ratio, and selective and sensitive methods to reduce false signals yet ensure a true signal is not missed.

Meaningful integration of travel and infectious disease propagation information is highly applicable to effective epidemiology and like an awareness of the course and speed of an enemy ship is to naval warfare, an understanding of the course and speed of disease transmission is needed for complete characterization and optimal intervention during an outbreak or attack. The development and integration of population dynamics, especially travel, should be considered essential function for a fully operational biosurveillance system and for effective epidemiology in the computer age.

The geography, demographics, relative centralization, transportation infrastructure, and highly refined tourism-based business focus have combined to make Las Vegas, Nevada a very suitable locale of interest for this research. Software tools have been prepared and tested which allow evaluation of the likelihood and timing of the spread of disease from an outbreak in Las Vegas to another city with emphasis on the projection of the spread of infection via surface and air travel.

The project was planned to leverage some existing technologies and add value with the development of new capabilities for: inter-city air and road travel modeling; intra-city travel and activity modeling, and; extended threat characterization to include the relationship between population movement patterns and infectious disease predictive modeling.

2.1 Background

The project proposed to include the use of regional demographics, transient population characteristics, tourism statistics, transportation data, and health and environmental monitoring data to develop the necessary information technologies and resulting prototype capable of modeling the spread of infection in a transient population. Timely threat containment must be the ultimate goal of surveillance therefore this demonstration project was proposed to investigate methods and develop related software to support improved intervention. Efforts included the work to define and validate functional and data requirements and to identify and assess the value of the available related datasets. The goals of the project were proposed to test and demonstrate the models and detection and characterization capabilities.

The project objectives include study of techniques and technology to represent travel modes to and from the Las Vegas study community, integration of population dynamics with existing biosurveillance methods, and working with local healthcare, transportation and hospitality industry stakeholders to establish the needed information sources. The community survey component of the research includes negotiating access to datasets and documenting issues and potential challenges to access. The project has made significant progress in obtaining, analyzing, and staging data, surveying data access issues, and in preparing software for the modeling and integration of travel functions with health surveillance.

This project leverages the unique characteristics of southern Nevada to study methods and develop capabilities useful to mitigate the effects of bio-weapons or pandemic disease. During previous efforts integration and tracking functions used semi-synthetic data, and regional and national summary data based on actual historic influenza-like-illness (ILI) summary reports to CDC, tourism, and air and road travel data. These historic temporal data for ILI, air travel, road traffic, and visitors were used to support the investigation of algorithms for probabilistic modeling of transmission routes and patterns and to support demonstration system development and validation while awaiting actual provider data access.

The research team investigated methods, information, and processing tools with potential to provide stakeholders with an understanding of the route and pace of transmission and functions to support intervention decision-making. The integration of a travel model with detection and characterization functions is being studied to determine the advantages and complexities. The project has undertaken the tasks of development and integration of travel functions in parallel with the study of health, visit, and travel information availability and quality.

The information study element of the project has included the interview of stakeholders and data owners to investigate technical, policy, and resource issues and constraints. This outreach activity has also sought to enroll stakeholders and data owners, and assess interface requirements and constraints. Project researchers have conducted a series of structured meetings with local stakeholders. Team members have visited local hospitals, clinics, and private practice physicians, as well as Nevada Department of Transportation (NDOT), McCarran Airport and major resort properties to investigate technical, operational, and policy issues related to surveillance and travel information access. These discussions were conducted in parallel with prototype development and demonstration-database development activities, and were necessary to enable the completion of representative datasets for system validation.

The data availability and quality study supports data synthesis and assessment of signal and noise characteristics. System and study design included the information and processing for detection, travel, information integration, and intervention planning with an emphasis on projection of the spread of infection through surface and air travel. This data was staged for use in both system demonstration and validation and for use in simulation and scenario evaluation.

A visitor population individual-level travel model was prepared, integrated and outputs evaluated. Originally hosted on a dual processor single computer, the individual-level predictive modeling codes were modified to run on a Hadoop cluster of twelve workstations (from surplus on another project). This resulted in performance improvement reducing simulation processing time significantly. This cluster was later moved to a set of five T110 Dell servers resulting in additional processing time reduction.

The contact rate study was conducted first for the visitors in various behavior demographics. Later the contact rate study was expanded to resident worker and visitor interaction including surveys of local strip businesses and conventions.

Codes were prepared for testing biosurveillance functions of detection and characterization with an emphasis on measurement of sensitivity, selectivity, and timeliness. Both univariate CUSUM and EWMA codes and multivariate MCUSUM and MEWMA process control codes were prepared for testing. These codes are currently being used for testing with syndromic time series data from five local hospitals over a five year timespan. Tests are being conducted and planned for all presenting, visitors only, residents only both unfiltered, parsed data and with pre-filtering. The plan includes testing of population and seasonal filters separately for comparison and in combination and evaluation of filter effects on outbreak detection.

2.2 Literature Review

Population figures based on public records and census are fixed values reflecting the number of people residing in an area. Actual daily population of a city or county varies based on resident travel, migration, visitors, commuters, birthrate, and mortality. These dynamics complicate the mathematical representation of infectious disease transmission. However, without such consideration the models of infectious disease transmission are incomplete. Korotayev (2006) offers encouragement noting that complex and chaotic behavior can be suitably represented at the macro-level by simple equations representing micro-level dynamics. This concept is applied to modeling as one seeks to represent system macro-dynamics by sufficiently modeling individual micro-level actions. Modeling when empirical data is incomplete due to business practice, privacy, competition, regulatory requirements, or resource constraints requires assumptions which in turn confound model validation (Camitz, 2010).

Much research using time-series detection methods relied on single variable approaches to obtain balance between speed and accuracy. Attempts to improve detection time without excessive false positives have led to the monitoring of more than one signal, which greatly reduces both the chance of missing an alarm and the likelihood of a false alarm (Wagner et al, 2006). Evaluating a sliding time window proved useful, but it became obvious that signal proximity had to be considered. This led to the study of algorithms for the detection of spatial and spatio-temporal clusters (Wagner, 2006, Kulldorf, 2005). Attempts have been made to model geographic spread of disease and spatial patterns of reported cases and potentially related variables, however cross correlation with local or long distance travel has not received significant attention (Carley, et al 2004).

Modeling infectious disease requires an understanding of human behavior and activities. While the severely ill can be expected to be less mobile (Longini et al, 2004) the mildly symptomatic and even those not infected, but coincidentally symptomatic, can drive the behavior of others by something as simple as a sneeze when the public is sensitized by knowledge of an outbreak, such as the during the recent novel H1N1 pandemic. At the macro level a pandemic or a smaller outbreak can be seen as an actor influencing an entity such as a city or a convention (Anolli, 2005). The spread of an infectious disease is; therefore, impacted by social interaction both at the level of physical location and at the level of individual and group perceptions. These factors affect transmission rate and more study appears to be warranted to support modeling of both normal, baseline behavior and altered behavior.

Magnusson (2005) stressed the need for more observation based study to improve models developed using purely statistical methods. Contact rate varies substantially based on simple social activity patterns. One influential pattern is the complex movement pattern of individuals and the resulting proximity of infectious and susceptible actors. Another important pattern is the effect of information on behavior. A search of the literature reveals little study has been conducted on movement patterns and human proximity.

The risk of spread of disease across geographic regions has increased due to the mobility of populations. Recommendations to control epidemic spreads by imposing travel restrictions, particularly for pandemic illnesses, must take care to account for economic costs (Epstein, et al, 2007). The literature indicates most surveillance systems which consider spatial information do so only to improve detection timeliness, specificity, and/or sensitivity and do not account for population mobility. Although cross contamination is not uncommon during the transit process, spatial spread is more likely to occur once the population has reached destination points (Body et al, 2008; Ellis, Kress, and Grass, 2004; Wenzel, 1996).

Proximity of passengers, travel time, susceptibility of passengers, and virulence of disease affect the transmission of virus from person to person. Even though the exchange of micro-organisms in pressurized cabin areas have been found to be lower than typical urban environments, the risk of exposure increases as time spent in air travel (Wenzel, 1996) and has been documented on flights in which the air circulation system has not functioned properly (Moser, et al, 1979). In studies where actual cases have been used to study transportation variables, the locations of individuals used for the study have either focused on a specific case study (Moser, et al, 1979), or a specific group of people (Rashid, et al, 2008). These types of studies are useful in understanding issues related to the single event exposure, but they do not necessarily account for specific travel patterns or focus on ways to improve surveillance.

While the concern about cross contamination among airline passengers is important, ultimately, the potential of exposed passengers and infected passengers to contaminate local populations is a serious public health concern. Most interest regarding the spread of disease as a result of airline travel has focused on progression of transmitting disease from one geographic area to another. Grais, et al (2004) modeled influenza forecasting based on air travel between specific American cities using data from the Centers for Disease Control and Prevention (CDC) and air traffic data from the Department of Transportation to predict outbreaks between specified large cities. Their findings indicated inconsistencies in their predictive modeling and recommended the utilization of their models as approximations of forecasting (Grais, et al, 2004). A study of the H3N2 flu virus documented the pattern of global circulation of the disease from east and Southeast Asia (Russell, et al, 2008).

Research does indicate that better tools are needed and as well as a better understanding of how the transportation network impacts the spread of disease (Hufnagel et al, 2004). They correctly note such research is essential to enable optimal intervention however, the value of travel restriction isn't necessarily well understood. Cooper et al (2006), argue air travel restrictions may be effective for SARS, but would not work to create a useful delay in the spread of influenza. These studies reflect valuable insights concerning the potential for, and limitations of, travel-restriction interventions. Unfortunately, studies do not necessarily account for specific travel patterns or focus on ways to improve surveillance. Other studies rely primarily on data provided by the CDC through the influenza surveillance system (Grais, et al., Brownstein). While these may be useful for developing models of transportation patterns, they do not provide the full picture of influenza and its relationship to travel.

Privacy protection issues surrounding surveillance of disease outbreaks related to hotel guests has been the subject of previous research. The European Working Group for Legionella Infections (EWGLI) created a surveillance network called the European Surveillance Scheme for Travel Associated Legionnaires Disease (EWGLINET) for reporting cases (Joseph and Rickets, 2009). This organization has been created to quickly identify and control for Legionnaires disease in the hospitality area (Cowgill et al., 2005). This European network has noted the sensitivity of the hotel industry in sharing information and has had a strict requirement for protecting privacy for clinical and travel data.

Disease outbreaks, of any size, can drastically affect a hotel and the consequences can be severe. EWGLINET was created to quickly identify and control for Legionnaires disease in the hospitality area (Cowgill et al., 2005). Once an outbreak has been detected, the accommodation site must go through a process to meet certain requirements in order to kill the disease and prevent it from spreading (Rota, Caporali & Massari, 2004). If these requirements are not met in a timely manner, the accommodation site's name will be placed on the EWGLINET's website (Rota, Caporali & Massari, 2004). In the United States, approximately 20% of reported LD cases were associated with travel (MMWR, 2007). The hope is that if clusters are detected early, the source can be quickly identified and treated. From a financial standpoint, hotels need to determine the source quickly so as to be able to return to normal business swiftly.

Transmission of influenza appears to be more closely correlated to air transportation flows rather than related to climate factors (Crepey and Barthelemy, 2007). Seasonal application of surveillance activities can also relate to airline travel. In the United States, influenza seasons are documented beginning October 1 of each year and are tracked for approximately 20 weeks, typically through mid-May (CDC, 2008). Research of airline transportation of the illness found that the rate of increased air transportation surrounding the Thanksgiving holiday serves as a modest predictor of influenza spread (Brownstein, Wolfe, and Mandl, 2006).

The 2009 H1N1 flu virus pandemic created a unique situation for modeling the spread of disease. In Mexico, especially the town of La Gloria, there began to be many cases of a respiratory illness. In La Gloria, 25% (591 cases) of the population became ill and the cause was discovered to be what became known as a novel H1N1 flu virus. Between March 10 and April 6, 591 flu cases were laboratory confirmed for H1N1 (Lopez-Cervantes et al., 2009). Cases were then found in the United States and Canada soon followed. By April 27, the first H1N1 cases in Europe were confirmed in Spain after 3 travelers returned from Mexico (Surveillance Group, 2009). In the United Kingdom, 65 cases were confirmed between April 27 and May 11 beginning with a couple returning from Mexico. France adopted an Influenza surveillance system in April after the first cases were reported around the world. By May 1, the H1N1 flu virus had arrived with travelers returning from Mexico. As of July 6, France had 358 confirmed cases with 261 of the cases attributed to travel in Mexico, the United States, Canada, South America, non-French Caribbean Islands, Asia, Oceania and the United Kingdom. The virus arrived in Greece by May 18 in a 19 year old male returning from New York City. The second and third cases were two students returning from the United Kingdom, making these cases the first to be associated with another European country. Australia and New Zealand have experienced a more severe outbreak of the virus. For the same time period, Australia and New Zealand had 8 times the amount of cases as the United States. According to the World Health Organization (2009), there were over 6,000 deaths in 199 countries caused by the novel H1N1 outbreak by November of 2009. This is a significant increase from May 2009 when the virus had only spread to 30 countries with a confirmed 5,231 cases (Boelle, Bernillon, & Desenclos, 2009).

The ease with which this virus was able to spread poses many challenges. No country or part of the world has been immune, reinforcing the need to study the effect that travel has on the spread of disease. Flahault, Vergu and Boelle (2009) created a metapopulation model to simulate the spread of disease through 52 major cities. The state of the disease as it progresses was tracked in each city, following the four states of disease. These states are Susceptible, Exposed, Infectious and Removed (SEIR). Following their study, the authors found that there would be two major waves of the H1N1 flu virus. The first would occur in the Southern hemisphere followed by a wave in the Northern hemisphere. The tropical cities would be faced with a more moderate activity and the wave is estimated to have a longer duration (Flahault et al., 2009).

The H1N1 virus is spread as other viruses and has many of the same symptoms as the seasonal flu which includes: fever, cough, sore throat, runny or stuffy nose, headache, chills, fatigue and body aches (CDC, 2009). The CDC also reported that most of the original calculations of the virus were probably underestimated, perhaps by as high as 140 times fold (Reed, et al, 2009). Among the groups with a major under-reporting were those most susceptible to the disease, the age 5-24 population. This is significant because the upper range of that age group would include a large proportion of Army personnel including 46% of the Army's enlisted personnel and 11% of its officers fall into that age category (Department of the Army, 2005).

According to the latest information on the disease, it appears likely that an infected person can be contagious usually from one day prior to showing any symptoms to 7 days after becoming symptomatic. Importantly, contamination of animate and inanimate objects must also be taken into consideration. Based on previous studies of influenza virus, it can survive on environmental surfaces and can infect a person for 2 to 8 hours after being deposited on the surface depending somewhat upon the ambient air temperature and relative humidity.

Assumptions are often made regarding mixing, contacts, and infection when modeling infectious disease. These assumptions mean transmission is an uncertain factor (Diekmann, 1996). This uncertainty is obvious when reviewing the discourse on influenza outbreaks. What is the actual incubation period? When does an infected become infectious? Does viral shedding occur at a fixed or variable intensity? Does sunlight or humidity significantly impact susceptibility or virulence? Is there heterogeneity within the infectious population resulting in varied efficiency between those who spread the infection? Does influenza actually transmit primarily by cough or sneeze? Is a passing contact sufficient for transmission or is length of exposure also a factor? (Armbruster, 2007) (Longini, 2004) (Moser, 1979) (Kenah, 2011) (Camitz, 2010). Contact requirements are also uncertain, but evidence supports a relationship between contact rate and outbreak intensity and duration (Haber, 2007).

Much retrospective influenza epidemic analysis refers to the reproduction rate or Ro. The analysis parameter Ro is a useful assumption and simplification. Ro supports comparative evaluation of separate influenza pandemics and assessment of potentially achievable immunity levels through intervention. Ro is often called the epidemic threshold, yet also the basic reproduction number, the reproduction rate, and the reproduction number. As Ro is calculated assuming an entirely susceptible population it is a term representing the relative potential for harm. However it is only in retrospect, when the harm can be quantified Ro can be estimated.

2.4 Methodology

The study was organized to investigate processes and technology useful to test proposed hypotheses. This included literature review, review of parallel research, development of models and simulators, and development and test of detection codes. The approach to test includes leveraging prior related research.

The principal hypothesis is modeling of a high-mobile, transient population can effectively represent the transmission of infectious disease or spread of biologic agents. A second hypothesis is the integration of high-fidelity event signals can validate the design and implementation of a biosurveillance system. The third proposed hypothesis is a predictive system can be used to characterize outbreaks more effectively and our fourth proposed hypothesis is predictive modeling supports timely threat containment.

Development of the mobility model began with the NDOT Annual Traffic Report for years 2005 through 2011. The automated traffic recorder section of the report includes a complete set of what the NDOT calls ‘comprehensive summary report’ pages from each of the ingress/egress routes for Las Vegas, Nevada. This information is organized by the ATR station number which is a unique identifier. Each ATR is further classified by its county, the functional classification of the roadway, and the ATR location. The Las Vegas metropolitan area can be accessed by a very limited number of major highway routes.

Typically less than half, in the past five years 43% - 47%, (GLS Research, 2008) of Las Vegas visitors travel by air. An air travel model was prepared beginning with study of the US Bureau of Transportation Statistics (BTS) data available online via queries and reports. The BTS data were used to create tables of aircraft types, seating configurations, and passenger capacity for each aircraft model and configuration used by airlines serving Las Vegas McCarran International Airport, airport code LAS. This study is intentionally focused on the airports and airlines having direct flights to and from LAS. Over the twelve year timeframe coinciding with the road travel model 297 US and international airports had direct flights to or from LAS with an annual average number of 220 airports serving passengers with direct flights to or from LAS during any single year within the model.

The research team sought to identify hotels that would be willing sources of information to improve the bio-surveillance picture. We identified 19 hotel ownership companies representing

40 different properties. Of these ownership chains, the largest in order of properties owned were MGM-Mirage (12 strip properties owned on the Las Vegas strip); Harrah's Entertainment (7 properties owned on or near the Las Vegas strip); Boyd Gaming (3 properties on/near Las Vegas strip downtown; 4 Coast properties owned, 2 near LV strip and 2 off strip properties); Wynn Resorts (2 properties on Las Vegas Strip); and Sands Corporation 2. The project team interviewed several security or risk management personnel and examined related artifacts to determine the types of information they collect on guests who become ill or injured, date and time of guest complaint/variance, whether they maintain this data in any storage capacity, how they respond to guests who become ill, the disposition of those guests, and both their interest and willingness to participate in the research project.

Project efforts included the development of software providing functions for air and surface mobility modeling and simulation of travel and infection in a locale of interest. Software codes were also developed to test detection and characterization efficacy using both univariate and multivariate algorithms. Due to the large number of datasets and the size of some of those datasets the time required to process data for simulation and testing was considerable. Some work was done to improve performance by standardizing the interfaces between components. This allowed distribution of application components over multiple processors. This did improve performance but the application's performance was mainly impacted by input and output requirements during simulation operation which were not significantly mitigated by process distribution. The input-output processing issue was addressed by parallel processing and by using the Map-Reduce feature of a Hadoop cluster.

Test Overview

Evaluation of hypothesis one will be supported by all planned testing and specific tests include MCUSUM and MEWMA and univariate CUSUM and EWMA detection codes. These tests will be used to determine the value of separation of visitor and resident populations for detection and pre-filtering time series data based on population dynamics as well as seasonal effects. Time to signal, missed outbreaks and false positives will be measured. CUSUM and EWMA codes have been prepared in JAVA and MCUSUM and MEWMA codes have been prepared from MATLAB codes by porting those codes to GNU Octave.

Evaluation of the second hypothesis is planned to employ semi-synthetic data and high-fidelity outbreak signal injection. Codes have been prepared in GNU R to produce synthetic time series and outbreaks. Preliminary tests with provider data indicate the preparation of the synthetic series is straightforward, but zip code association is not addressed in the literature and must be preserved for this study.

Evaluation of hypotheses three and four, and support for evaluation of hypotheses one will be provided through the use of the predictive individual-level model. Tests are in progress using historic CDC ILI data and both road and air travel data to model the paths and pace of infectious disease spread through travel. This input-output (I/O) intensive model is hosted on the cluster to leverage the Hadoop Map Reduce feature to allow parallelization of the I/O and processing.

These tests are either in progress during the preparation of this report or data and coding issues are being resolved. Corrective actions related to test codes is required due to the characteristics of the provider data. Other issues with test preparation include the parsing and grouping of the data into bins representing syndrome categories.

2.5 Analysis

2.5.1 Provider Data Summary

The following report summarizes the syndromic time series data from participating providers and was prepared by Dr. Chris Cochran of UNLV.

Christopher R. Cochran, Ph.D.; Subcontractor PI
University of Nevada Las Vegas
School of Community Health Sciences

Bio-Surveillance of a Highly Mobile Population
Understanding Influenza and Influenza-like (ILI) Symptoms

Influenza is considered a seasonal illness typically spanning October 1 – Mid-May of each year. Therefore, for historical data collection purposes, annual influenza and influenza-like illnesses must be categorized in the appropriate time frame. The Centers for Disease Control and Prevention (CDC), monitors influenza from state and local health departments, federal agencies such as the Department of Defense and Veterans Affairs, and sentinel sites including physician offices, health care clinics, hospital emergency departments and urgent care facilities, and the Department of Defense and Veteran's Affairs (CDC, 2008). According to the CDC, ILI includes fever, headache, fatigue, cough, sore throat, runny or stuffy nose, body aches and diarrhea and vomiting (more common in children than adults). They note that it is impossible to diagnose flu based presence of symptoms alone because other diseases can have similar symptoms. The only way to confirm influenza is through the use of clinical testing (CDC, 2008).

It is our intent to develop a system whereby patient visits can be submitted for the project that relate to influenza like illness (ILI) on an ongoing real time or near real time basis. To develop and adequate model for understanding visitor utilization of local hospitals and providers, the project also sought to collect historic patient visit information for the previous five years. By obtaining patient zip codes as part of the data collection process, an analysis of the number of visitors utilizing health care providers can assist in developing the transportation model. This analysis will also allow us to compare how well chief complaints match up to diagnoses.

Based on four- year data trends as reported by the Nevada State Health Division, reports of ILI illness have increased significantly at the beginning of each year, typically around the 10th week of the influenza season. In Figure 1, the actual peaking of ILI begins in early December, then drops slightly during the holidays and begins to show rapid acceleration at about week 3 of the at the beginning of the year. This is notable because the Las Vegas visitor volume drops during the month of December then picks up significantly in January (LVCVA, 2008).

<u>Data Needs</u>

ILI typically refers to fever and one of the following: headache, cough, sore throat, runny/stuffy nose, body aches, diarrhea and vomiting. However, some symptoms may not be present during patient visit and diagnosis may reflect a more general description such as lower respiratory infection, pneumonia, or upper respiratory infection. To that end, the project needs to identify all complaints that can fall into the ILI category. For the purpose of this study the following data needs were identified:

- Pseudonymized linker (patient de-identifier measure)
- Event time and Place (for the patient encounter)
- Age. Age may be an important components since children, for example, may have different influenza like symptoms (e.g., vomiting) than adults.
- Zip code. 5-digit zip code or 3-digit for sparsely populated zips.
- Patient classification. Hospital patient classifications generally include emergency room, inpatient, outpatient, or other services such as laboratory or radiology. In this case, only emergency room classifiers are necessary since we are primarily interested in ambulatory patients. Outpatient information would typically apply only for follow-up visits. Inpatient classification may be useful, but not necessary for this project.
- Chief complaint. This is the patient reported reason for seeking care. Key for this project. Need to understand how this information is collected and coded. (See section on ICD-9 coding criteria).
- Illness onset by date/time (desirable for this study but is not routinely collected for electronic data entry). Probably would require review of physician, nursing or triage notes.
- Diagnosis/Injury code. Diagnosis or diagnoses assigned from patient visit. This is the billing code that will be the most reliable for case identification and confirmation. However, the availability of this data will vary from hospital to hospital.
- Diagnosis type (preliminary, interim, final, admitting).
- Diagnosis date/time. Should be easily available for date. May not be consistent for time.
- Discharge disposition. Essential element but may only be known as admitted to hospital, sent home, AMA, other).

To determine the locale of visitors and potential onset of their illness, other useful information would include visitor place of stay, days since arrival, and days until departure.

Data Collection and Methodology Techniques

Hospital emergency room data for the years 2006-2010 were used for this study. The data was compiled from hospitals that have the closest proximity to the Las Vegas, NV strip corridor. All hospitals included in this study are located within (X) miles of that corridor. Through interviews with local resort security operators, Southern Nevada Health District, and emergency services personnel, these hospitals were identified as having the greatest likelihood of providing emergency services to visitors residing on the strip corridor: University Medical Center, Sunrise Medical Center and Sunrise Children’s Hospital, Desert Spring Medical Center, Valley Hospital and Medical Center, Spring Valley Medical Center.

An IRB from the previous study was updated and resubmitted to the UNLV Office for the Protection of Human Subjects prior to the collection and received final approval by the UNLV IRB in October of 2011. Final approval of the IRB project from the Human Subjects Protection Scientist (General Dynamics) Human Research Protection Office (HRPO), Office of Research Protections (ORP), U.S. Army Medical Research and Materiel Command (USAMRMC) was given approval in February of this year. Therefore, data collection for the project was delayed until the final approval from the sponsor agency.

Data files were transmitted through secure email files with expiration dates upon acceptance of the files from UMC and Valley Hospital. Data from Sunrise Hospital was transmitted into a CD. Data was formatted into Excel comma delimited files.

UMC has been a partner in this project since project year 1. Both UMC and Sunrise Medical Center represent the largest hospitals in Southern Nevada thus experience higher volumes of emergency room visits. UMC also operates a level one trauma center, but data from that emergency unit is not included in this analysis since it is not likely to have The data from all other hospitals was collected during the third funding year of this project. Desert Springs Medical Center, Valley Hospital and Medical Center and Spring Valley Medical Center are all part of the Valley Hospital Systems (VHS). The data collected from these hospitals was provided by their central data source. All data providers were given the data elements for the collected data. Some fields were inconsistent and one of the most important data components, “Chief Complaint”, was available for only one year of the VHS data. Data was collected in an excel data delimited format.

In the period 2006 – 2010 the number of visitors to Las Vegas ranged from just over 36 million more than 39 million per year. The period 2007 to 2009 saw decreasing number of visitors to Las Vegas due primarily to the economic recession. However, in 2010 the numbers began to climb again to more than 39 million visitors, still below the averages of 41 million tourists reported in our previous study.

For this study, data was collected for a five year period from the hospitals for the period 2006-2010. The data elements considered in this study included the following:

De-identified patient code, admission date, admission time, discharge date, Chief Complaint, up to five diagnosis (ICD-9) billing codes, age, sex and patient zip code.

There are some gaps in the data that will be addressed in a follow-up report. These gaps include missing data for 2008 from the VHS hospitals and missing data from 2006 from Sunrise Hospitals. The table below illustrates the data collected from the hospitals. The data indicates that more than 15% of the ER visits to area hospitals are by visitors (see Table 1).

Table 1 – Hospital emergency room utilization by local residents and visitors

			HOSPITAL					
			UMC	SUNRISE	SPRING VALLEY	VALLEY	DESERT SPRG	Total
local	0	Count	27901	74924	32287	23310	22399	180821
		% within HOSP	8.4%	15.8%	20.5%	14.4%	21.4%	14.7%
		% of Total	2.3%	6.1%	2.6%	1.9%	1.8%	14.7%
	1	Count	302691	400438	125010	138175	82092	1048406
		% within HOSP	91.6%	84.2%	79.5%	85.6%	78.6%	85.3%
		% of Total	24.6%	32.6%	10.2%	11.2%	6.7%	85.3%
Total		Count	330592	475362	157297	161485	104491	1229227
		% within HOSP	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
		% of Total	26.9%	38.7%	12.8%	13.1%	8.5%	100.0%

The addition of the other hospital data suggests that an even greater volume of patients visit the private hospitals than visit the county's only public hospital. This may be due likely to the overcrowding of the public hospital and the insured nature of the area's visitors. But the additional data is of major importance in trying to determine the utilization of Southern Nevada hospital emergency rooms by visitors to the community. An analysis was conducted to determine the top DRG elements for the report. Based on the information provided, the following indicate the main codes billed by the hospitals (Table 2).

Table 2: : ICD Code Frequency of Visitor Utilization of Hospital ERs

		University Medical Center		
Rank	ICD-9 Code	Diagnosis	Frequency	Pct.
1	789.00	Other symptoms involving abdomen and pelvis	31182	7.5
2	780.6	Fever and other physiologic disturbances of temperature regulation	15830	3.8
3	729.5	Pain in Limb	14985	3.6
4	786.2	Cough	13809	3.3
5	V71.4	Observation following other accident	13163	3.2
6	787.03	Vomiting alone	10250	2.5
7	784.0	Headache	10087	2.4
8	780.60	Fever and other physiologic disturbances of temperature regulation	9151	2.2
9	724.5	Fever and other physiologic disturbances of temperature regulation	8794	2.1
10	786.50	Chest pain	8372	2.0
		Sunrise Hospital and Medical Center		
Rank	ICD-9 Code		Freq.	Pct.
1	V71.9	Unspecified Diagnosis	12785	2.7
2	465.9	Acute upper respiratory infections of multiple or unspecified sites	10281	2.2
3	305	Nondependent abuse of drugs	9090	1.9
4	648.93	Issues of Pregnancy	9053	1.9
5	780.6	Fever and other physiologic disturbances of temperature regulation	8518	1.8
6	786.59	Other discomfort in Chest	8408	1.8
7	786.5	Chest pain	7005	1.5
8	599	Other disorders of urethra and urinary tract	6440	1.4
9	382.9	Other symptoms involving skin and integumentary tissues	6108	1.3
10	780.2	Syncope and collapse	5965	1.3
		VHS Hospitals		
Rank	ICD-9 Code		Freq.	Pct.
1	789	Other symptoms involving abdomen and pelvis	16581.0	3.1
2	305	Nondependent abuse of drugs	12758.0	2.4
3	786.59	Other discomfort in Chest	10644.0	2.0
4	786.5	Chest pain	8740.0	1.6
5	465.9	Acute Upper respiratory infection	7806	
6	780.2	Syncope and collapse	7195.0	1.3
7	599	Other disorders of urethra and urinary tract	6748.0	1.3
8	784	Symptoms involving head and neck	5758	1.1
9	V68.9	Unspecified administrative purpose	5065	0.9

*10th ranked in VHS unable to determine.

The data in the tables above illustrate one of the major problems in using ICD9 data codes for early identification of outbreaks such as flu. While the data from the UMC hospital indicates a greater likelihood of potential influenza like illness (ILI), the data from all of the other hospitals appears to be more consistent in their reporting measures. To calculate the data included in these tables, an analysis was conducted of all ICD-9 codes provided (up to 6 codes in some cases). One of the limitations of this data pertains to the Valley Health Systems hospitals which only reported on ICD-9 code for their cases. Thus, it is possible that inclusion of more than one code would have captured a truer assessment of the patient services. In examining the data from the other hospitals, the great majority of cases had more than one ICD-9 code reported, thus, it appears unlikely that the cases provided in the VHS hospitals' data would have included less than one code. It is also possible that coding errors, changes in data collection system formats, or other factors including time needed for proper data submission contributed to the lack of multiple codes in these cases.

In Table 3, we sorted the top ten ICD primary complaint code (the first billing code assigned to patients). In this table we use only the first ICD-9 code due to missing values from the VHS hospitals.

Table 3: Top ICD-9 Codes, Visitors vs. Local Residents for primary ICD-9 code

Visitors (2006-2010)				Local Residents 2006-2010			
Dx		Freq.	PCT.	DX	Code	Frequency	Percent
Nondependent abuse of drugs	305	9008	5	Unknown DX	V71.9	31180	3
Syncope and collapse	780.2	5406	3	Other symptoms involving abdomen/stomach	789	24062	2.3
Unknown DX	V71.9	3749	2.1	Other discomfort in chest	786.59	20042	1.9
Other discomfort in chest	786.59	3597	2	Other symptoms involving abdomen/stomach	789	16122	1.5
Chest pain	786.5	2848	1.6	Chest Pain	786.5	12907	1.2
Other symptoms involving abdomen/stomach	789	2657	1.5	Other disorders of urethra and urinary tract	599	12627	1.2
Symptoms in digestive sys	787.03	2445	1.4	Flu Symptoms	465.9	11789	1.1
Other gastrointitis	558.9	2263	1.3	Issues of soft tissue	729.95	11630	1.1
Other disorders of urethra and urinary tract	599	2077	1.1	Nondependent abuse of drugs	305	11542	1.1
Contusion	920	1578	0.9	Chest Pain	786.62	10613	1
Pneumonia (#12)	486	1483	0.8	Fever	780.6	10150	1
Acute sore throat NOS (#18)	462	1162	0.6	Acute sore throat (NOS) (#22)	462	6923	0.7
Flu symptoms (#24)	465.9	994	0.5		784	9998	1
Fever (#25)	780.6	940	0.5		780.2	9056	0.9

Based on the numbers in the table, the types of illness diagnosed indicate very little difference in frequency after the top 10 codes. For the visitors data, we included the code for the flu related symptoms which rank 24th on the list as well as some prominent ILI type symptoms. A complete list of these codes for up to 5 diagnostic codes will be provided in our final report.

Identifying Cases from Chief Complaints

This preliminary analysis is critical to the early detection of any cases beyond the norm. Often, a patient may present to the emergency room with full knowledge of their condition, but cases related to flu may not be so clear. When considering ILI conditions, a number of symptoms may contribute to an ultimate detection of a case. However, some cases may be vaguer. Cough, for example, is a vague symptom taken by itself because the condition may be caused by other, sometimes similar respiratory illnesses such a bronchitis or allergies. However, based on most of the literature, the combination of cough and other symptoms, especially fever, can be a good indication of flu. To ascertain the chief complaints that could more reliably be considered a chief complaint of flu, we first had to isolate specific terms in the chief complaint. Based on previous literature reviews, we selected those terms that were most likely to be used in describing symptoms of flu. The most obvious were those cases in which the chief complaint was flu or influenza. Next, we compiled cases using specific symptoms in some string of the data. Those symptoms included the following:

- COUGH
- COLD
- FEVER
- RUNNY NOSE
- WEAKNESS
- BODY ACHES
- SORE THROAT
- HEADACHE

Those codes cases were then recalculated into a binomial using 1 for the presence of the symptom and 0 if the symptom was not present. Based on those findings, we then merged data by using the following combinations (examples are shown based on the merged data sets from UMC and Valley Hospital where 1 = the presence of two or more symptoms and 0 = no ILI symptoms:

FLU

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1225522	99.7	99.7	99.7
	1.00	4055	.3	.3	100.0
	2.00	2	.0	.0	100.0
	Total	1229579	100.0	100.0	

FEVER

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1184095	96.3	96.3	96.3
	1.00	45484	3.7	3.7	100.0
	Total	1229579	100.0	100.0	

RUN_NOSE

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1227436	99.8	99.8	99.8
	1.00	2143	.2	.2	100.0
	Total	1229579	100.0	100.0	

BODY_ACHE

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1228192	99.9	99.9	99.9
	1.00	1387	.1	.1	100.0
	Total	1229579	100.0	100.0	

SORE_THT

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1219788	99.2	99.2	99.2
	1.00	9791	.8	.8	100.0
	Total	1229579	100.0	100.0	

COUGH

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1202635	97.8	97.8	97.8
	1.00	26944	2.2	2.2	100.0
	Total	1229579	100.0	100.0	

STUFFY_NS

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229408	100.0	100.0	100.0
	1.00	171	.0	.0	100.0
	Total	1229579	100.0	100.0	

VOMITTING

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1228176	99.9	99.9	99.9
	1.00	1403	.1	.1	100.0
	Total	1229579	100.0	100.0	

Any data in the table above indicates that of 1,229, 579 cases examined, more than 91,000 hospital visits included at least one of the symptoms for ILI. Any cases resulting in a score of 2 or more could be considered the combination necessary for determining flu. The result was 2,319 cases for the two hospital systems. That data was then merged with those cases that were classified as flu or influenza:

FEV_STUFFY

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229569	100.0	100.0	100.0
	1.00	10	.0	.0	100.0
	Total	1229579	100.0	100.0	

FEV_RUNNY

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229399	100.0	100.0	100.0
	1.00	180	.0	.0	100.0
	Total	1229579	100.0	100.0	

FEV_THROAT

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1228953	99.9	99.9	99.9
	1.00	626	.1	.1	100.0
	Total	1229579	100.0	100.0	

FEV_COUGH

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1226649	99.8	99.8	99.8
	1.00	2930	.2	.2	100.0
	Total	1229579	100.0	100.0	

COUGH_THRT

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229102	100.0	100.0	100.0
	1.00	477	.0	.0	100.0
	Total	1229579	100.0	100.0	

COUGH_STUFFY

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229559	100.0	100.0	100.0
	1.00	20	.0	.0	100.0
	Total	1229579	100.0	100.0	

COUGH_RUNNY

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229197	100.0	100.0	100.0
	1.00	382	.0	.0	100.0
	Total	1229579	100.0	100.0	

COUGH_ACHES

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229504	100.0	100.0	100.0
	1.00	75	.0	.0	100.0
	Total	1229579	100.0	100.0	

FEV_ACHES

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229438	100.0	100.0	100.0
	1.00	141	.0	.0	100.0
	Total	1229579	100.0	100.0	

THROAT_ACHES

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1229518	100.0	100.0	100.0
	1.00	61	.0	.0	100.0
	Total	1229579	100.0	100.0	

When combined with the flu and influenza variables, the total number of cases is approximately 2,300 cases. In the table below, the variable ILI_COMBO represents the number of ILI related cases through the merging of those variables with at least two symptoms of flu. The data indicates that 4,649 cases can be realistically classified as ILI.

ILI_COMBO

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1224930	99.6	99.6	99.6
	1.00	4649	.4	.4	100.0
	Total	1229579	100.0	100.0	

By combining the ILI designated illness with the flu, and sore throat admissions the following results are concluded:

THE_FLU

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.00	1212224	98.6	98.6	98.6
	1.00	17355	1.4	1.4	100.0
	Total	1229579	100.0	100.0	

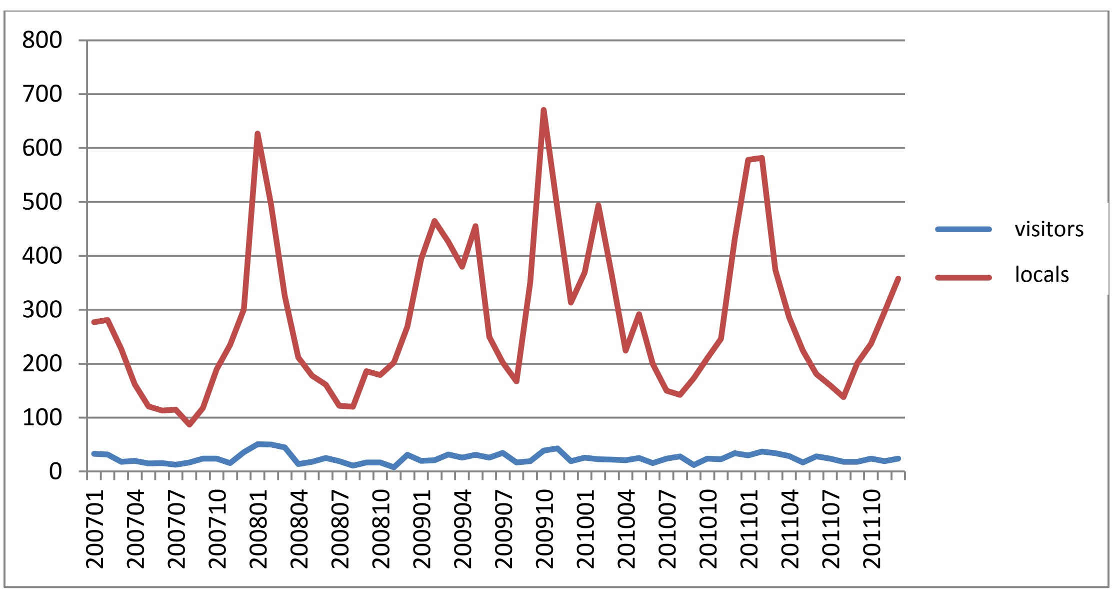
The following table shows a preliminary assessment of the cases classified as influenza for both visitors and local residents.

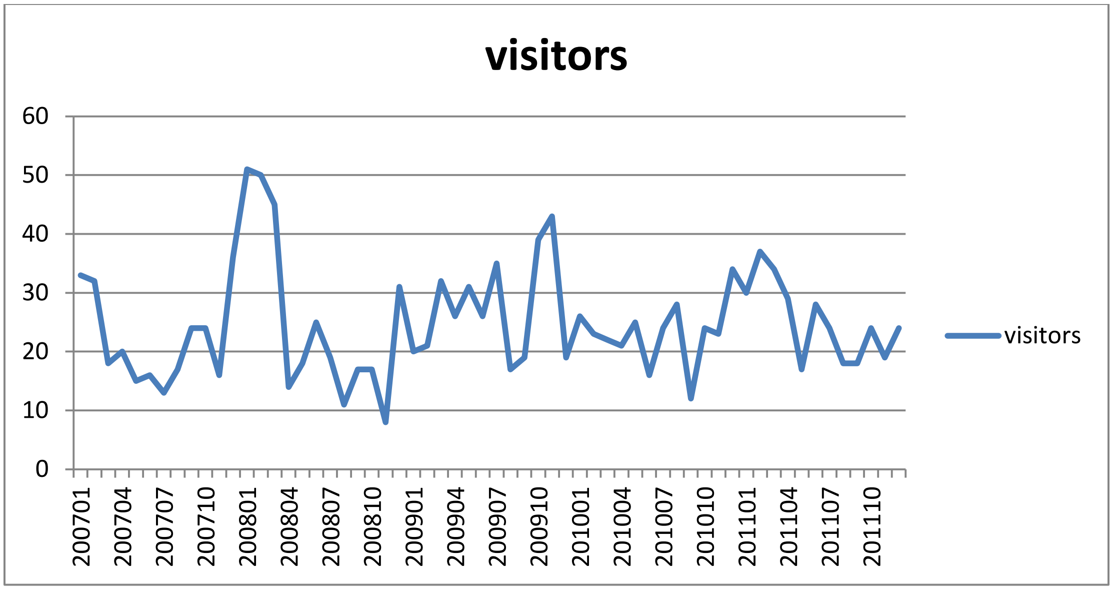
THE_FLU * local for Locals and Visitors

			local		
			0	1	Total
THE_FLU	Local	Count	178864	1033360	1212224
		% within THE_FLU	14.8%	85.2%	100.0%
	Visitors	Count	2011	15344	17355
		% within THE_FLU	11.6%	88.4%	100.0%
Total		Count	180875	1048704	1229579
		% within THE_FLU	14.7%	85.3%	100.0%

<u>Flu Trends 2006-2010</u>

In the two line graphs below, the trends for the outbreak of flu are illustrated. The first graph describes the frequency of flu tracking the outbreak between visitors and local residents. The next graph illustrates the trends for visitors based to provide a better relationship with the local resident trends. The graphs illustrate the changing basis of flu on an annual basis. In most years, outbreak among visitors peaked before the outbreak among local residents. However, during certain years, outbreaks among visitors seem to show a more erratic trend. This may be due to the time of year when certain outbreaks happen in different parts of the country. Further assessment of this data is warranted.





Limitations of the Data

There can be several important limitations to the data collected thus far. First, the data sets are large and many records require additional data cleansing to format data file mergers into a more reliable file. Because of the size of the data files, it is much more difficult to create accurate coding techniques to adequately capture chief complaints that might be indicated such as “flu”. For example, on examining all records related to “flu”, about 15% of the cases had to be omitted because of the inclusion of “fluid” or “flutter” in the chief complaint. Moreover, some terms such as “I feel terrible might ultimately be coded as flu, but these are not captured in recoding string data into nominal data elements.

Second, any system based on hospital or clinic data has inherent delays based on the medical seeking behavior of the infected individual. In addition to the incubation period of the disease, there are delays in the seeking of medical care. The first step in a person’s illness usually involves self-care and possibly over the counter (OTC) medications. This step may last from several hours to several days, and in many cases, is the only step involved in the infected person’s medical care.

Third, if a person does decide to seek medical care, there are delays in transportation to the medical clinic and delays in the admissions process. These delays are usually not significant in the overall course of the illness, but are relevant to the frequency of data transmission and analysis. If data provided need to first be coded by hospital staff (such as an ICD9-CM diagnosis code), there are additional delays of hours to days.

Fourth, reliability of data - Some of the challenges to achieving real-time data surveillance when gathering information from EDs are that symptoms and CC are often recorded free-hand and there are no standardized terms so aggregating the data can become difficult. This is consistent with previous research regarding surveillance issues (Travers et. al, 2006). We also found that some information may take days or weeks to be transmitted due to not updating the patient record or deciding ICD-9 codes. Final diagnosis may depend on the reimbursement rates or how well the illness was charted. Although ICD-9 codes are standardized, the process of assigning patients ICD-9 codes involves multiple people and can take longer than desirable (Travers et. al, 2006).

Much more work remains to be done on this study. The project team will delve further into the chief complaint data to make sure that we are able to identify more cases of flu or ILI that may be lost to data manipulation ore missing data fields. In addition, the team hopes to add additional missing data from the hospitals to make a more accurate time line calculation.

2.5.2 Contact Rates

Report on Continuing Contact Rate Research

Henry Osterhoudt, PhD

Residents Working on the Las Vegas Strip

During research to support our biosurveillance project we needed the figure of Las Vegas residents who worked on the Las Vegas Strip, The area on Las Vegas Boulevard from the stratosphere Tower on the North to Mandalay Bay on the South. Data was readily available for employees working in casinos from research done by the Center for Gaming Research at The University of Nevada Las Vegas (UNLV). That total was 120,000. The number of Las Vegans working for non-casino entities; however, was not available.

To find this number Dr. Henry Osterhoudt conducted a survey of all the businesses on the strip. The survey included: retail outlets (stores, kiosks, and mini-marts), restaurants (fast food and sit down), night clubs, valet parking, tour companies, ticket vendors, rental agencies, massage parlors, street performers, street vendors, motels , tattoo parlors, and time shares. The researcher visited 642 separate businesses. The number constitutes all the businesses on the strip including those physically located in resorts but not owned by the casino corporation. These entities rent space from the resort but are owned by a separate entity. The number includes all the businesses in the various malls along the strip: Stratosphere Tower Shops, Fashion Show Mall, The Grand Canal Shoppes at the Venetian, The Shoppes at the Palazzo, The Forum Shops, Via Bellagio Shops at Bellagio, Miracle Mile Shops at Planet Hollywood, Crystals at MGM Mirage City Center, and Mandalay Place at Mandalay Bay. In addition other casinos have groupings of shops in or adjacent to their properties, for example between Wynn and Encore or between Luxor and Excalibur. At each business the researcher asked a responsible manager or the person manning the business or kiosk how many people worked at the establishment in a 24 hour period. Some of the establishments had business hours ranging from 8 to 16 hours. Some were open 24 hours a day.

The survey took three weeks and determined that a maximum of 20,156 individuals work on the strip in non-casino owed businesses on any given 24 hour period.

Contact Rates for Convention Attendees

Researchers surveyed contact rates for convention attendees in Las Vegas. The research was done during the Consumer Electronics Show (CES) 10-13 January 2011 and during observations of smaller conventions at various resorts during the year. The CES is a huge convention staged at the 3 million square foot Las Vegas Convention Center (LVCC) which includes 2 million square feet of exhibition space and 243,000 square feet of meeting rooms and the 2.2 million square foot Venetian Convention Center. The show was attended by over 150,000 people. During the convention researchers acted as convention goers and recorded their contacts in two ways. The first set of numbers was determined by counting the total number of contacts that came within three feet of the front of the researcher. The numbers were recorded over a three day period as the researcher acted as a convention attendee arriving at the convention, registering, and then touring all the exhibits. The second set of numbers was determined as those contacts that lasted longer than three minutes. This set was determined by simulating a convention goer who was conversing with convention vendors or listening to vendor presentations. As in the research of gamers the largest numbers of contacts were accumulated during transit of the convention. Researchers recorded their contacts in 15 minute intervals from the time they exited their vehicles until they returned to their vehicles at the end of the day. Researchers were Las Vegas residents and thus not staying at a resort hotel. Contacts tallied 357 per hour although the numbers varied greatly depending on whether the researcher was actually moving about the convention or simply getting there or returning to their transportation.

The contact rate dropped markedly when the time of 3 minutes was included as a parameter. Researchers began their research by attempting to count both types of contact but quickly realized that this was extremely difficult so a separates effort was made to specifically determine the contact rate only for the three minute parameter. This contact rate was significantly smaller than the prior rate with an average of 3 to 6 per hour. Estimating the number of convention goers who experienced this contact rate was possible only by an educated observation, not an actual count. The estimate is about 15% of convention goers seemed to be in this category. But the figure could skew higher.

As with gamers the majority of contacts were experienced while traversing the convention. Choke point and popular exhibits also contributed to the larger numbers as did the huge number of attendees who taxed even the huge capacity of the LVCC. This convention was one of the largest in total attendance, but it is not out of the norm for contacts of attendees. Smaller conventions use smaller venues, but the contacts of attendees are similar. Movement and choke points at the various venues in Las Vegas, each casino resort has some convention or meeting space which accommodate various size meetings or events, are for the most part consistent in elevating contact rates. It should be noted; however, that architecture does affect contact rate to an extent. Newer convention and meeting facilities are designed with larger hallways, more spacious meeting rooms and multiple routes of ingress and egress. The sum total of these architectural advances is to decrease the contact rates for transiting conventioneers and meeting attendees. Older facilities, many of which are still in use, do not have the wider routes and more spacious venues of the newer properties. For the largest conventions which all use the LVCC convention facilities this increases the contact rate because the Las Vegas Hotel and Casino, Previously the Las Vegas Hilton is an older facility and is contiguous to the LVCC. The LVCC itself is a huge facility but it encompasses routes which constrict movement of huge convention audiences and it does not have sufficient dining venues to handle the huge crowds for the largest conventions without congestion. In fact although the LVCVA tries to alleviate the congestion as much as possible additional dining venues would not prove viable. Likewise the Sands Expo Convention Center is an older facility and it like the LVCC has its share of chokepoints even though the resorts to which it is connected, The Venetian and The Palazzo, are brand new and state of the art.

In addition the growing number of attendees at some of the more popular events; the CES is a good example, contribute to the crowding. The LVCVA attempts to alleviate this problem by expanding the convention to multiple venues at different locations. The problem is that at any convention certain exhibitors have more popular exhibits than others and these exhibits whether because of the exhibitor or the product cause conventioneers to congregate at those locations. At the CES new electronics (The LG exhibit for example) and new vehicles drew capacity shoulder to shoulder crowds. In some cases exhibitors who have exhibit space near entrances to the convention floors, space which is highly desired, also contribute to congestion as attendees crowd together to observe the displays or the interactive experience. Again savvy exhibit designers seek to grab and hold the attention of attendees and occupy the space near the entrance contribute to the congestion largely by design. These factors, despite the best efforts of the event organizers, greatly effect congestion and drives up contact rates.

Additionally at the LVCC security is tasked with admitting only authorized attendees. At each entrance security personnel check identification badges. This creates bottlenecks and further contributes to elevating contact rates as attendees queue up to enter the convention hall or go from one building to another. Each entrance has another security checkpoint and the identification process is repeated.

Conventions habitually last for a period of days which also elevates contact rates. Meeting and events which last for one day do not afford the attendees sufficient exposure time to effect an increase in contact rates so a multi- day convention is the most representative and the best laboratory in which to determine an accurate effective rate.

Most studies of disease have assumed a homogeneous contact rate instead of doing the research to accurately determine the actual rate of contacts. This study has done extensive research to provide actual data that models subject behavior. Our researchers have spent a good deal of time modeling both gamer and convention attendee behavior on the Las Vegas strip. We have used data gathered by both the Las Vegas Convention and Visitors Authority and the University of Nevada Las Vegas Center for Gaming Research to focus and refine our research. This data served as a departure point to permitting our personnel to maximize the effectiveness of our activities. For example we knew percentages of gamers who played various games so we were able to focus on behavior of gamers who played the most popular games thus providing the largest sample of visitor behavior. We also knew the size and frequency of conventions and the use of convention and meeting space so we were able to most effectively employ our researchers to acquire real contact data.

3.0 Key Research Accomplishments

Completed investigative meetings with hospitals, clinics, physician practices, paramedics, Nevada Department of Transportation, airport, and hospitality industry representatives

Updated surface travel database and added second half 2008 and all 2009 and 2010 information

Updated air travel database for system test adding 2009 and 2010 data

Updated simulator ILI files using CDC sentinel data for 2008, 2009, and 2010

Prepared and maintained message server, provider (UMC) ED data interface, and database

Continued requirements analysis and updated system functional requirements

Conducted and documented a literature review of related research and publications

Conducted an empirical study of Las Vegas Strip employment including non-resort business, convention attendance, and interaction between residents and visitors to improve understanding of contact rates

All staff completed two CITI training courses for research protection

Updated and submitted protocol to UNLV IRB for approval to access and use provider ED data

Received UNLV IRB protocol approval

Submitted UNLV IRB approved protocol to Office of Research Protection for approval to access and use provider ED data

Received ORP decision of Non-Human Use data

Completed ED data normalization, anomaly removal, binning of syndromes, and preliminary data analyses in preparation for test

Evaluated some available, existing biosurveillance codes for suitability including SYDOVAT, Trisano, Real-time Outbreak Detection System, EpiFire, Global Epidemic Model and Global Influenza Surveillance Network

Ported and tested synthetic data generation codes using R to prepare synthetic test data sets with appropriate distributions and effects

Ported MATLAB MCUSUM and MEWMA codes to Octave

Developed EWMA and CUSUM detection codes

Developed software code for state-space disease model with mobility between cities and models for SECIR adding carrier-latency and SEInR including variable infectivity

Modified software codes for simulation of air and road travel to improve performance. Converted single-computer designed codes to run on the Hadoop cluster for performance improvement and developed some of the new modules required to run biostage codes on the cluster

Updated the Hadoop cluster hardware to reduce travel simulation time

4.0 Reportable Outcomes

Received Non-Human Use ruling from Office of Research Protection

Established interface with the County hospital system and obtained and stored year of ED data

Obtained ED data from University Medical Center, Sunrise hospital, and three Valley Health Systems hospitals

Completed prototype software for modeling population mobility and correlation of travel and outbreak information sets

Prepared test software codes for outbreak detection and conducted initial validation testing

Completed prototype software for modeling population mobility and simulating outbreaks

5.0 Conclusions

As this report is being prepared there are four weeks of funding remaining for this effort and there is a monthly progress report due next week. The final report is due in July however, work is planned to be completed within the next two or three weeks which will enable submission of the final report by June. Presentation, analysis, and discussion related to the results of tests will be included in the final report.

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